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An empirical study of electricity and gas demand drivers in large food retail buildings of a national organisation

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ABSTRACT

Food retail buildings account for a measurable proportion of a country's energy consumption and resultant carbon emissions so energy-operating costs are key business considerations. Increased understanding of end-use energy demands in this sector can enable development of effective benchmarking systems to underpin energy management tools. This could aid identification and evaluation of interventions to reduce operational energy demand. Whilst there are a number of theoretical and semi-empirical benchmarking and thermal modelling tools that can be used for food retail building stocks, these do not readily account for the variance of technical and non-technical factors that can influence end-use demands.

This paper discusses the various drivers of energy end-uses of typical UK food retail stores. It reports on an empirical study of one organisation's hypermarket stock to evaluate the influence of various factors on annual store electricity and gas demands. Multiple regression models are discussed in the context of the development and application of a methodology for estimating annual energy end-use demand in food retail buildings. The established models account for 75% of the variation in electricity demand, 50% of the variation in gas demand in stores without CHP and 77% of the variation in gas demand in stores with CHP.

1. Introduction

Currently in the UK there are more than 9000 food retail stores with sales floor areas of more than 280 m^2. Most of these stores are operated by the four largest supermarket multiples: Tesco (29.7%), ASDA (17.7%), Sainsbury's (17.0%) and Morrisons (11.8%) [1,2]. The remaining 23.8% are shared by smaller chains such as Waitrose and Iceland [2]. The energy consumption of these stores is important for the profitability of their organisation as their operating margins are generally low at an average of 4.2% in 2005 [3]. Additionally the consumption is important for national CO_2 emission targets where the food retail sector accounts for more than 3% of the total electricity consumption in the UK and approximately 1% of total UK CO_2 emissions [4]. Considering both these issues, along with the relative homogeneity of management structures and energy end-uses in food retail organisations, minimising and managing energy demand is an important opportunity for both business competitiveness and national targets.

Strategic financial planning in the sector's large organisations typically takes account of future demands for gas and electricity. Future demands and financial implications are estimated for different time frames, such as the months or year ahead, and account for increasing energy prices, changes in store sizes and reductions due to investment in energy efficiency initiatives applied across an organisation's building stock. Projected energy demands are used for multiple purposes including the identification of the operational efficiency of individual stores indicating generally where inefficiencies lie and when faults occur. With such multiple purposes and scope of applications, the energy demand tools-developed to estimate future demands-need to be able to provide insights on many technical and non-technical factors that influence gas and electricity demand. The aim of this study is to identify and interpret the implications of key factors influencing the aggregated annual electricity and gas demand, in a sample of large food retail stores of a national food retail organisation. This

Abbreviations: AHU, air handling unit; CDD, Cooling Degree Days; CHP, combined heat and power; HDD, Heating Degree Days; HVAC, heating, ventilation and air-conditioning; MPAN, Meter Point Administration Number; SFA, sales floor area.

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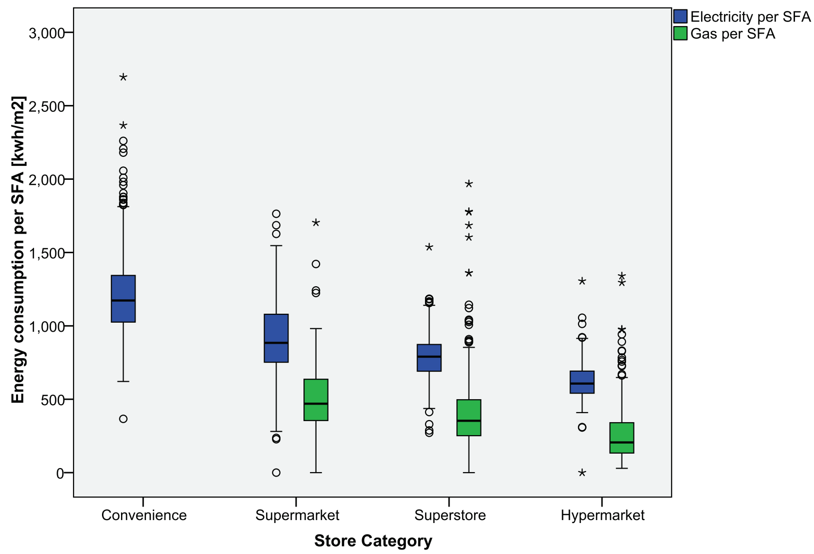

Fig. 1. Electricity and Gas Intensity of for each store category.

Table 1
Retail store categories.

Category	Sales floor area (m^2)
Convenience store	<280
Supermarket	280–1400
Superstore	1400–5750
Hypermarket	>5750

will inform the further development of new energy budgeting and management tools for the organisation.

Related studies reported in the literature tend to focus on detailed levels of analysis and factors to establish causal links with end-use demands, for example [5–8]. This study backtracks somewhat to investigate demands and drivers at the aggregated annual level. In doing this, causal links are suggested where their relative significance is evaluated in the context of the range of functions of such models.

The organisation's retail building stock studied here is comprised of four different store formats, which can be aligned with the common categories based on sales floor areas as shown in Table 1 [9]. Whilst there is a high degree of heterogeneity across the store categories, this reduces when inspecting the stock within each category. Store formats differ in terms of size, location, proportion of total floor area for different functions (e.g. frozen food, non-food, home delivery, back office, stores), external lighting provision, in-store services (e.g. in-store bakery, fish/meat/delicatessen counters), opening times, building type (e.g. new build, redevelopment from previous different use) and on-site services (e.g. petrol station, car wash, home delivery, click and collect). As a result of these differences the composition and intensity of energy end-uses varies across the store categories but have comparatively less within each category.

Convenience stores are the most common category of stores in the organisation's stock, numbering more than 2000 (more than 50% of the total stock) [10]. They are usually found close to the consumer; either located within a town centre, close to apartment blocks, or as part of petrol filling stations. Their product ranges, and thereby also in-store services, depend on the local market demand. They are typically closely related to their location in urban centres and are mostly chilled-food dominated as they bring the classic lunch meal to their customers. These stores are electrically heated.

Supermarkets are the most individual store category. These stores are usually found within town centres and the building types vary from new, purpose built stores to refurbished buildings such as churches. Similar to superstores these stores include a mixture of in-store services, depending on their location and market demands. Typically they have an in-store bakery but not any fish, meat or delicatessen counters and are a mixture of gas and electrical heating with some having a small number (i.e. one or two) ceiling mounted, cassette type cold air recirculating units for local cooling.

Superstores are the second most common store category, and are found closer to the consumer, usually at the edge of the town centre, and are typically built for purpose. In rare cases some of these stores were acquired from previous owners and refurbished to meet the organisation's design standards. These stores include a mixture of in-store and on-site services, as well as a mixture of construction types, as they can be timber framed, or simple steel framed retail sheds. The majority of these stores are heated by a central gas system, and approximately 15%[1] of them have a combined heat and power (CHP) plant. Cooling is provided by centralised constant volume air conditioning systems.

Hypermarkets are the largest retail stores within the studied stock. These are usually located outside town centres - normally at the edge of the town- and are designed for purpose, thereby maintaining the organisation's and national building standards at the time of construction. Being the largest stores of the stock, they contain the full range of in-store and on-site services, such as petrol filling station, in-store bakery, fish; meat & delicatessen counters as well as significant non-food sales area, including clothing departments and electronics departments. Although all hypermarkets have similar product lines, the proportional composition of these varies. In general, these stores have similar on-site electrical and gas end-uses; therefore have a lower relative variance in average Electricity and Gas Intensity. Approximately 75% of all hypermarkets are open 24 h a day. The majority of these stores are heated by a central gas fired low temperature hot water (LTHW) system with 15% having a CHP engine installed that generates electricity and heat. Cooling is provided by centralised constant volume air conditioning systems with vapour compression chillers.

This study is the first stage of a larger project, which seeks to develop an energy-forecasting tool for the organisation's entire stock of food retail buildings. This study focuses on hypermarkets

[1] Iain Black, Mechanical Engineering Manager, Tesco PLC, Personal communication, 2/10/2012.

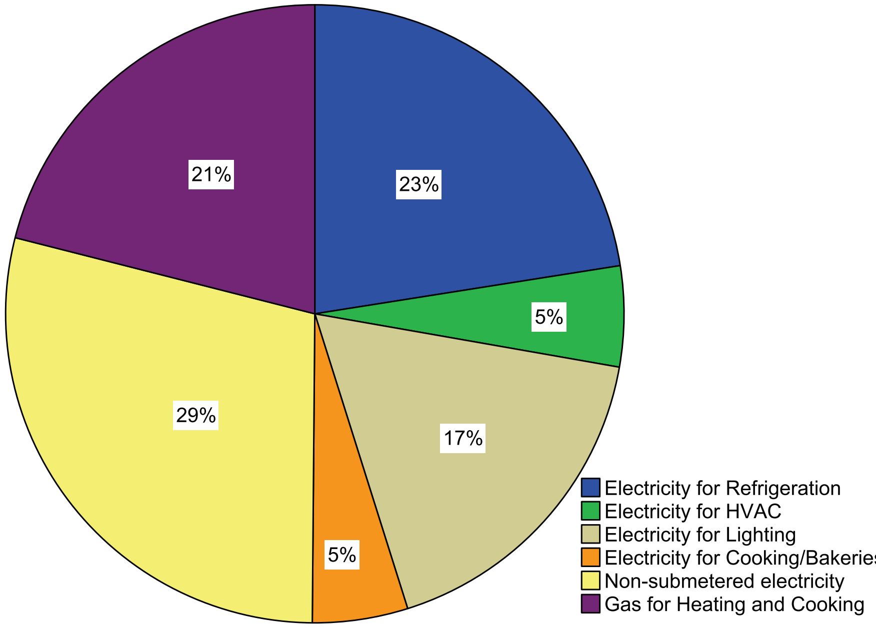

Fig. 2. Breakdown of average annual end-use demands in hypermarkets.

as they have a smaller variation in electricity and gas intensities compared to the other store categories found in the organisation's stock, see Fig. 1, which indicates that signals of correlations will be stronger and more readily apparent than with any of the other store categories. The energy demand of hypermarkets will be discussed further in Section 2, while data and analysis methods are explained in Section 3. Results are presented and discussed in Section 4. Section 5 concludes the work.

2. Energy demand in hypermarkets

The energy end-use demand of food retail stores is usually met by a combination of electricity and gas. A sizeable body of work has been developed in the literature on electricity demands in food retail stores but much less has been reported on gas-fuelled end-uses. Typically gas accounts for a 20% of the total energy demand in hypermarkets as shown in Fig. 2.

2.1. Electricity

Electricity typically accounts for more than 70% of the energy consumed in UK supermarkets [4], and for approximately 80% in the study sample. An average hypermarket consumes 4.1 GWh of electricity per year. The main end-uses include refrigeration, heating, ventilation and air-conditioning (HVAC), lighting, and other general e.g. socket outlets, cash registers, and specialist in-store services such as bakeries or large kitchens serving either customer or staff restaurants. The percentage contribution of each end-use depends on the range and relative magnitude of end-uses present in a store. For example, Tassou et al. [4] report that refrigeration accounts for 29% of electricity demand in a hypermarket that contained a customer restaurant and a bakery, whereas refrigeration accounting for over 50% of electricity in modern supermarkets has also been evidenced [11]. Whilst refrigeration is typically reported as being the largest energy end-use in all store categories, other electrical end-uses can be significant.

2.1.1. Refrigeration

Most large retail stores provide chilled and frozen products in display cases held at high (+3 to +5 °C) and low (−18 to −22 °C) temperature. The condenser and compressor elements of the refrigerant circuits are located away from the sales floor area, either in an enclosed plant room or in the open outdoors. This ensures that heat taken out of the circuits does not add unnecessary heat gains to the chilled or frozen food sales areas. The evaporator elements are built into the chilled or frozen display cases in the sales areas.

The load on refrigeration circuits for chilled and frozen cases is mainly driven by conditions of the local thermal environment at both evaporators and condensers. At evaporators, i.e. chilled or frozen food cases in sales areas, heat is gained from the local environment around cases through radiative, convective and conductive heat transfer [12,13]. At the condenser elements, the rate of heat taken out of the refrigerant circuit is a function of the temperature difference between the refrigerant entering the condenser and the local ambient air temperature, and the rate of airflow, driven by condenser fans, across the condenser heat exchanger. The amount of heat gained is influenced by usage in terms of how often customers remove products and staff restock cases. During these actions the amount of warmer air circulating into a case increases thereby increasing, albeit to a small extent, the load on the refrigeration circuit. As the local ambient temperature increases the amount of heat taken out of the refrigerant decreases, which increases either the number of condenser fans running or increases the load on the compressor.

Refrigeration load has also been shown to be influenced by relative humidity which affects both overall refrigeration loads [11] and more specifically the electrical demands on anti-sweat heaters and defrost cycles [14]. As low temperature systems, for frozen food, typically consume more electricity than high temperature systems, for chilled food, the mix/ratio of low temperature to high temperature cases influences the total refrigeration load of a store [4].

Overall the interdependence between each element of low and high temperature refrigeration systems means that a rise in external temperature can affect refrigeration electrical loads. At evaporators, this is through increased local temperatures around cases in sales areas and usage patterns; at condensers, it is through condenser fans having to provide increased air flow rates over condenser heat exchangers; and at compressors, it is because greater work is needed to condition the refrigerant to the required level for return to the evaporators.

Chilled food cases also incorporate lighting and circulation fans, which are a comparatively small component of the total electrical demand for refrigeration systems. At an aggregated level, total electrical energy demand for individual cases has been found to be correlated with the total display area of individual cases [15].

2.1.2. Heating, ventilation and air conditioning

Heating, ventilation and air conditioning in food retail buildings provides thermal comfort for customers and staff. Conditions necessary for products that are sensitive to temperature and humidity are maintained within separate dedicated conditioned spaces, such as cold rooms and refrigerated display cases. As stores are effectively large open plan boxes, giving maximum flexibility of space use to the retailer, large-scale convection heating and cooling is provided by centralised air systems. These centralised air systems provide heating and cooling to sales floor areas.

In the sample studied, all heating and cooling is provided to the sales floor area via bespoke packaged air handling units (AHUs). These units have a fan section and mixing box, a heating coil and a cooling coil with dedicated condenser and compressors as part of the air-handling package. The fan is fixed speed, and the mixing box has dampers set to constantly provide a fixed ratio of 1:3, fresh air to re-circulated air, in order to meet the ventilation guidelines for supermarkets [16]. The air-handling units distribute conditioned air via high-level ductwork to sales floor areas.

AHU heating coils are serviced by LTHW from a gas fired boiler circuit, thereby being a component of the overall gas demand. Where the store has a CHP installed, the CHP is the lead boiler in the LTHW circuit. The air-handling units temper incoming fresh air by mixing it with warm stratified air. The amount of heat added to the supplied air is modulated through the heating coil to ensure sales floor area temperature set points are maintained.

AHU cooling coils are direct expansion circuits operating on a conventional vapour-compression refrigeration cycle, thereby being a component of the overall electricity demand. To supply cooling to the sales floor areas, the mix of fresh and re-circulated air is passed over the cooling coil, in which the refrigerant temperature is modulated as a function of the amount of cooling needed. To minimise the cooling demand of cooling coils, cold air is extracted from the refrigerated aisles via an extract path underneath the refrigerated cabinets. This cool air is returned to one of the AHUs and mixed with incoming fresh air.

In order to prevent ingress of cold outdoor air around entrance areas, warm air curtains are used at the main entrance and warehouse doors of each store. The heating for these is provided by either the LTHW circuit, thereby being part of the gas demand, or via electric heaters, thereby being part of the electricity demand.

Temperature set-points for heating and cooling are set remotely (19 °C in the heating season and 24 °C in the cooling season), in accordance with recommended levels by CIBSE Guide A [17] and follow a company-wide strategy, therefore it is assumed that all stores are maintained at the same internal temperature.

2.1.3. Lighting

Lighting includes in-store lighting, lighting for the back offices and storerooms, as well as for perimeters and car parks. Lighting is controlled so that certain lux levels are met during the main opening hours: 8 am to 10 pm. Lux levels are then reduced between 10 pm and 8 am in 24 h stores. When stores are closed, stocking lighting is in place, which is significantly lower than the trading lux level. Lux levels are set according to the guidelines in [17].

In recently built stores there is a trend towards the control of some in-store lighting as a function of daylight conditions. In these situations lighting controls harness the daylight benefits of store designs whereby facades with large areas of glazing allow daylight to penetrate a portion of the sales areas. In these situations a number of rows of artificial lighting, close to glazed areas, are automatically controlled so that when minimum in-store lighting levels are met by daylight some rows are automatically dimmed. This modulation of artificial lighting provision can significantly offset the lighting load.

Specialist accent lighting is also increasingly used to differentiate particular products or enhance visual colouring and quality of fruit and vegetables in many stores. This involves the use of discharge lamps mounted in down lighters, operated during the main opening hours. Such accent lighting is in addition to standard sales floor area lighting.

Lighting is also provided around the perimeter of stores and associated car parks following the BS5489-1.2003: Code of practice for the design of road lighting [18].

Whilst overall lighting is a significant component of total store energy demand, i.e. 17% on average, and a direct function of opening hours, the proportional influence is dependent on the store's format and use of automated daylight linked controls.

2.1.4. Specialist services

Stores of all scales have various specialist services, which can be defined as non-standard service or product lines. For example, some larger stores have customer restaurants whilst some smaller stores have customer coffee machines. The existence of these has an effect on comparing electricity demand, at an aggregated total store consumption level between stores of similar types. Specialist store services include:

- Customer restaurants
- Petrol stations
- Photographic printing
- Deli/meat/fish counters

2.1.5. Non-submetered consumption

Other electrical end-uses common in all stores are those that are required for the retail function, including check-outs; control and security systems; telecommunications; storage areas and small power outlets both on sales floor and in the back office areas are typically non-submetered. Equipment that would usually fall in any of the above categories, Sections 2.1.1–2.1.4, but have been replaced after the installation of submetering can also sometimes appear in the non-submetered category due to incorrect re-installation of metering.

2.2. Gas

As mentioned earlier, gas accounts for about 20% of the energy consumed in the study sample, an average hypermarket consumes 1.8 GWh of gas in a year. The main end-uses include heating and specialist in-store services such as bakeries and cooking facilities, but the percentage contribution of each end-use is not clear, as gas consumption of the study sample is not sub-metered.

2.2.1. Heating

Heating in the sample of hypermarkets studied is mainly provided by LTHW heating coils, as mentioned in Section 2.1.2 above, and is therefore part of the gas demand. In a proportion of the stores, heating from warm air curtains, located over store public entrances, is by centralised gas fired LTHW circuits. Whilst the heating energy demand of these is expected to be highly sensitive to outside air temperature the small amount of resultant gas demand is too small to be evident in a store's total aggregated annual gas consumption.

2.2.2. Cooking

Cooking and baking are the secondary uses of gas in most large stores. Cooking includes cooking of food for the employees in the employee canteen, the dinners in the customer restaurant, as well as cooking of ready-made foods, such as hot chicken and bakery products. Bakery products include fresh bread and other bakery and confectionary goods.

2.2.3. CHP

A number of stores have gas fired combined heat and power (CHP) systems that generate heat and electricity for use onsite. These systems are sized to meet a portion of the heat demand of a store and generate this as a by-product of generating electricity thus offsetting some of the electricity demand from the national network [19,20]. The organisation uses a company-wide strategy for the operation of the plants therefore it is assumed that all CHP plants were operated under the same strategy during the year of data collection for this study. The CHP plants included in the sample use gas for the generation of electricity, it is therefore expected that these stores will consume more gas than the stores without a CHP system.

3. Data and analysis methods

3.1. Drivers of energy demand

In order to build a model to estimate energy demand, i.e. total annual electricity and total annual gas, the first step is to identify the factors that influence these demands at the aggregated level. Whilst these can be identified from theoretical concepts of energy performance and preliminary correlation tests, the availability of relevant data and information limits the factors that can be used to investigate what drives variation in these energy demands. This has implications for casual links between factors and end-use energy demands. It is assumed that the drivers of the various end-use energy demands described in Section 2, will have a measurable influence on total electricity and gas demands. These end-use related drivers can be grouped into those that describe physical characteristics (*Physical* variables), such as size and thermal performance, those that represent the operational characteristics of individual stores (*Operational* variables), such as the opening hours, and those that describe the location characteristics of the stores (*Regional* variables). A summary table of all factors is included in Table 2.

Table 2
Dependent and Independent variables.

	Type
Dependent	
Electricity demand (kWh)	Continuous
Gas demand (kWh)	Continuous
Gas Intensity (kWh/m^2)	Continuous
Independent	
Physical	
SFA (m^2)	Continuous
Total floor area (m^2)	Continuous
Year of construction	Continuous
Pre-Post 2002 (pre = 1, post = 0)	Dichotomous
Ceiling Height (m)	Continuous
No. of Trading Floors	Dichotomous
Food: Non-Food Ratio	Continuous
CHP (yes = 1, no = 0)	Dichotomous
Electrical rating (of CHP plant) (kWe)	Continuous
Operational	
Opening hours (24 h = 1, not 24 h = 0)	Dichotomous
Volume of Sales (£)	Continuous
Sales/SFA (£/m^2)	Continuous
Regional	
CDD	Continuous
HDD	Continuous
Easting (hm)	Continuous
Northing (m)	Continuous

3.1.1. Physical

In any building stock populated by one building type, such as the study sample of hypermarkets, store size would be expected to influence total electricity and gas demand, where the scale of the demand is more clearly a function of the overall size and the thermo-physical characteristics of the building envelope. Whilst store size, in terms of total floor area and sales floor area is readily available in centralised databases, the thermo-physical characteristics of envelope elements, i.e. surface areas; thermal conductance; solar transmission; orientation and exposure, are not. To overcome the absence of information and data on these primary drivers of heating and cooling the *Year of Construction* was identified as an indicator of energy related thermo-physical characteristics of a store's envelope, similar to what was used by Chung et al. [5]. This is because even though energy related design regulations and the organisation's standards have changed over time for efficiency or architectural reasons, stores built within a year are very similar. The main step change in these regulations and standards occurred in 2002 when envelope energy related specifications were enforced by the organisation; new specifications required stores to have higher ceilings and be of steel frame and panel construction instead of brickwork. Because of this whether a store was built or refurbished before or after 2002 (*Pre-Post 2002*) was adopted as a dichotomous independent variable.

Additionally as the stores in the study sample all have centralised air systems, heating and cooling load is also a function of the amount of air that is heated or cooled, which can be represented by a store's volume, as discussed in [21]. As the volumes of conditioned spaces in each store were not readily available the assumption was adopted that store volume is an approximately linear function of ceiling height (*Ceiling Height*) and was therefore included. Ceiling Height does not fully represent the volume of air in the stores, as some stores have mezzanine levels, therefore the *No of Trading Floors* was also included as a factor to investigate that relationship.

Although *Total Floor Area* defines the overall size of a store and therefore the scale of energy related end-uses, not all spaces in a store are conditioned therefore it is usual practice to account for sales floor area (*SFA*). SFA is usually considered to be half of the total floor area of a store [22,23]. While the influence of floor area (total and sales) on total energy and energy intensity should differ it is also possible that energy intensity is an inverse function of floor areas as efficiencies of scale will provide a degree of efficiency.

It is expected that stores with a larger area for refrigeration cases will consume more electricity. As a variable to represent the ratio of refrigerated to ambient sales floor areas was not available, an indicative variable of *Food: Non-Food Ratio* was adopted. This was selected because a number of food products usually need to be kept in cooled conditions. However, by way of example, electrical products are typically associated with electricity consuming TV walls.

As noted in Section 2.2.3, CHP plants are present in some of the studied sample and have the effect of increasing gas demand compared to stores without as some of the additional gas is consumed in generating electricity. The extent of this effect on gas demand is a function of the size of the CHP plant. To account for this the *Electrical Rating*, i.e. an indicator of CHP size, was included in the analysis of stores with CHP. The electricity produced by the plants is metered and combined with the electricity consumed from the grid for the purposes of this study; therefore the presence of a CHP plant does not affect the total electricity demand of the store.

Table 3
Beta weights of annual electricity demand.

	Beta weights			Collinearity statistics	
	B	Standard error B	Beta	Tolerance	VIF
(Constant)	6.12×10^5	2.12×10^5			
SFA (m^2)	3.11×10^2	3.15×10^1	0.636	0.315	3.179
Volume of Sales (£)	1.40×10^{-2}	2.00×10^{-3}	0.352	0.362	2.763
Food: Non-Food Ratio	3.51×10^5	6.78×10^4	0.278	0.452	2.213
Pre-Post 2002	-2.07×10^5	6.87×10^4	−0.132	0.682	1.467

3.1.2. Operational

Opening hours can be expected to have a direct impact on aggregated energy demand as when a store is closed the end-use energy demands for heating, cooling, lighting (internal and external), sales systems, restaurants, etc., are reduced; recorded hours of occupancy were also used by [24]. As the stores in the sample vary between conventional opening hours and being open 24 h *opening hours* was included as a factor.

During day-to-day operation of a store the number of customers can affect various end-use energy demands. Heating and cooling is affected by heat gains from customers within conditioned spaces whilst heat losses can be affected by the opening of entrance doors as customers enter and leave a store. The end-use demand in customer restaurant's kitchens is also be affected by the number of meals prepared. In a similar way, the load on refrigerated cases is affected by heat gains when customers open and close doors on frozen food cases and when frozen and chilled cases are restocked. Whilst some of these effects may be minimal and difficult to identify in the signal of variations in end-use energy demands, the proxy indicator of *Volume of Sales* was selected to represent the scale of customers moving in, through and out of each store.

3.1.3. Regional

As discussed in Section 2, outdoor temperatures can influence refrigeration and HVAC loads, depending on the systems in place. For that reason, stores were divided according to their geographical location, adopted from [25], and Cooling Degree Days (*CDD*) and Heating Degree Days (*HDD*) were computed for each region with a base temperature (T_{base}) of 15.5 °C, using the online tool developed by BizEE Software [26]. Whilst the base temperature of any building is unique, being a function of a buildings particular heat gains and losses, the threshold of 15.5 °C is commonly adopted for the UK climate [25]. The expectation is that as CDD increases, stores use more electricity for cooling, and as HDD increases, stores use more gas (or electricity) for heating. Nevertheless, internal air temperature was not included as a factor, because as mentioned in Section 2.2.1 most of the stores are remotely controlled and are expected to have the same internal air temperature at any given time.

Easting was selected as the difference in longitude between the westernmost part of the UK and the position of the store, while *Northing*, is the difference in latitude between the southernmost part of the UK and the position of the store. Both were included in the set of independent variables to represent the location of the stores.

All variables, unless otherwise stated, were sourced from readily available sources, e.g. the organisation's centralised databases. *Electricity Consumption* was measured at the Meter Point Administration Number (MPAN) using wireless loggers. Data was collected weekly for each hypermarket and summed over a period of 365 days to generate annual consumption data. Where a CHP plant was present, electricity generated from the plant was metered separately and added to the MPAN value. Total annual *Gas Consumption* for each store was provided by the supplier and verified from the in-store gas meter by an independent consultant.

3.2. Analysis methods

Measurements of all variables were compiled for each hypermarket store, ($N = 215$). The study dataset was then checked and adjusted for quality and outliers. From the initial sample, stores with missing values were removed ($N = 12$), similar to stores that had undergone any type of development works (extension or remodelling) within the period investigated ($N = 9$). With the remaining dataset standardised procedures were used to detect outliers where any data values more than 3 standard deviations from the mean were individually investigated. Whilst most of the data points falling outside of this range were found to be valid measurements, a number of these ($N = 6$) were not. These were found to be measurements of stores within shopping centres where it is possible that the measurements included consumption of the whole shopping centre and not just the stores in question, and therefore they were removed. This procedure ensured that stores that had experienced technical faults or structural changes in end-use energy systems or measurement systems were removed from the study sample dataset. This resulted in a complete study sample for electricity of $N_{elec} = 188$ and a study sample for gas of $N_{gas} = 123$, as complete gas consumption data was not available for a further 65 stores.

All variables were tested for normality and linearity and it was confirmed that all dependent and independent variables fulfilled the requirements of parametric tests, except *Gas Consumption*. *Gas Consumption* was found to have a bimodal distribution, which when investigated revealed significant differences between stores with CHP plants and those without. Separate analysis was therefore carried out for stores grouped according to the presence or absence of a CHP plant.

Statistical tests were applied to groups of dependent and independent variables to identify correlation significance of store characteristics and drivers of demand and goodness of fit of resultant regression equations. The dependent variables investigated were *Electricity Consumption* and *Gas Consumption*. Stepwise linear regression was used to identify significance of proposed independent variables which were selected on the basis of engineering understanding of electricity demands along with factors identified in other studies as discussed in Section 3. These tests informed the design of multiple linear regression models where analysis of the dependent variables resulted in three parallel equations; the independent variables included in each equation varied in relation to the dependent variables being investigated.

Stepwise linear regression, along with regression diagnostics, was conducted using SPSS (Version 19). This automated procedure resulted in automatic exclusion of independent variables that were computed to be statistically insignificant. Regression diagnostics were used to scrutinise resultant regression statistics for linearity, normality, homogeneity, collinearity and signularity.

4. Results and discussion

Stepwise multiple linear regression was conducted using the full model of all variables listed in Table 2. Through this procedure

Table 4
Beta weights of annual gas demand intensity (stores without a CHP).

	Beta weights			Collinearity statistics	
	B	Standard error B	Beta	Tolerance	VIF
(Constant)	4.08×10^2	6.47×10^1			
SFA (m^2)	-2.30×10^{-2}	6.00×10^{-3}	−0.373	0.688	1.454
Food: Non-Food Ratio	4.43×10^1	1.25×10^1	0.325	0.858	1.166
Ceiling Height (m)	-1.85×10^1	5.29×10^0	−0.283	0.888	1.127
No of Trading Floors	-2.68×10^1	1.37×10^1	−0.156	0.664	1.506

those variables that did not have statistical significance were removed from the regression models. The selected variables were then introduced into a standard regression analysis. Whilst this procedure removes variables that have weak signals in the dataset it is possible that influential factors are not accounted for, because they were found to be statistically insignificant in the regression models. This could be because the type of variables available in the dataset does not suitably represent them. This issue was considered when interpreting the results that follow.

4.1. Total annual electricity demand

Total annual electricity demand was found to be a function of physical size, Volume of Sales, composition of sales areas and factors related to year of construction. The resultant regression model, Eq. (1) shows 44.6% of the variability in *Electricity Consumption* is accounted for by the *SFA* of a store, and an additional 26.3% is accounted for by the *Volume of Sales* of a store. The addition of the *Food: Non-Food Ratio* increased this by 3.7%, while the addition of the *Pre-Post 2002* factor increased it by 1.2%.

$$\begin{aligned}\text{Electricity Demand [kWh]} &= 6.1 \times 10^5 + 3.1 \times 10^2(\text{SFA } [\text{m}^2]) \\ &+ 1.4 \times 10^{-2}(\text{Volume of Sales } [£]) \\ &+ 3.5 \times 10^5 \ (\text{Food : Non-Food Ratio}) \\ &- 2.1 \times 10^5 \ (\text{Pre} - \text{Post } 2002) \qquad (1)\end{aligned}$$

This model accounts for 75% (R^2_{adj}) of the variance in Electricity and is significant ($F(4,183) = 146.251$, $p < 0.001$). *SFA* and *Volume of Sales* have the greatest effect on the *Electricity Consumption*, with standardised β weights of 0.636 and 0.352 respectively ($p < 0.001$), Table 3, while the *Food: Non-Food Ratio* has a smaller but still significant effect of 0.278. Pre-Post 2002 has a significant but negative effect of −0.132, which means that stores built after 2000 consume less electricity than stores built before 2000. The effects of all the included independent variables are significant at the 0.001 level.

This model is considered to be moderate to good as few variables prove to be statistically significant and half of the variables have comparatively large regression coefficients, i.e. of the scale of 10^5 kWh/yr for one unit variance. The model also shows that factors related to the composition of product lines, i.e. Food: Non-Food Ratio, and the thermo-physical properties of construction, i.e. Pre-Post 2002, do have a statistically significant influence on total annual electricity demand. This is as expected but as Year of Construction proved not to be significant the indication is that overall influence of construction properties is less than that of other factors.

Although the influence of SFA is as expected, i.e. the larger the store the more electricity it consumes, the strength of influence of this is less than expected. This is considered to be due to the impact of store volume, usage intensity and composition of product lines not being linear functions of SFA. In terms of electricity demand, where the size of cooling coils, the amount of cooling needed and the size of fans can be expected to have direct influence on HVAC electricity demand; increasing the volume of air to be conditioned in a store would result in increasing the total electricity demand. In other words, if stores had a linear relationship between SFA and store volume the relationship between SFA and electricity demand would be stronger. Similarly, composition of product lines, represented by the Food: Non-food Ratio, can affect the relationship between SFA and electricity demand. This is because whilst Food: Non-food Ratio indirectly reflects the relative extent of store floor area dedicated to refrigerated products, such that increasing proportions of floor areas dedicated to food products can be expected to result in increasing refrigeration demand, this ratio is independent of SFA. Usage intensity or footfall, as indirectly represented by Volume of Sales, can be expected to directly impact a number of electricity end-uses such as refrigeration, HVAC and cooking in restaurants. As this is not a linear function of store size (SFA), being more directly related to usage intensity, it also affects the relationship between SFA and total annual Electricity Demand.

A similar situation was found with usage intensity, as represented by Volume of Sales, where the relationship between usage and electricity demand was found to be statistically significant but not as strong as expected. This is likely because electricity end-uses that are directly affected by usage, in terms of the number of people using a store (i.e. HVAC, specialist services and other, for more specific end-uses within these categories see Section 2.1), are relatively small components of total electricity demand and, in the case of refrigeration being the largest end-use, usage has a smaller direct impact.

Local climatic conditions would be expected to have a direct influence on HVAC cooling loads however the variables used to represent this, i.e. HDD, CDD, were found to have no statistical significance. This is considered to be partly due to HVAC being one of the smallest components of annualised total electricity demand, see Fig. 2, and that CDD and HDD are not normally distributed across the study sample. With HVAC being such a small component of aggregated annual electricity demand yet being the end-use demand most directly associated with outdoor temperature the statistical signal can be expected to be weaker than other end-use causal influences. It is be expected that the correlation exists but it is simply too small to emerge explicitly at the aggregated annual level. As an example this is a common finding when relating aggregated annual data with small scale but theoretically important factors.

Overall the multiple linear regression analysis of total annual electricity demand indicates that at the aggregated annual level, electricity demand can be reasonably well estimated by some but not all of the factors that would be expected on the basis of building energy demand theories. For example, HVAC, an end-use directly affected by the thermal performance of a building's envelope and outdoor weather conditions, has a statistically insignificant impact on total electricity demand compared to the main electrical end-uses of refrigeration, lighting and specialist services.

In this annual electricity demand model, SFA and Volume of Sales could be expected to have a linear type of relationship, where Volume of Sales increases as the size of store increases, thus resulting in collinearity in the model. However, signals of such collinearity were not evident in the computed collinearity statistics, i.e. the VIF level for each variable is below an adopted threshold of

Table 5
Beta weights of annual Gas Intensity (stores with CHP).

	Beta weights			Collinearity statistics	
	B	Standard error B	Beta	Tolerance	VIF
(Constant)	7.77×10^{2}	1.36×10^{2}			
SFA (m^2)	-4.90×10^{-2}	1.20×10^{-2}	−0.498	0.475	2.105
Electrical rating (kWe)	1.19×10^{0}	3.10×10^{-1}	0.344	0.957	1.045
Food: Non-Food Ratio	9.02×10^{1}	3.80×10^{1}	0.298	0.884	1.131
Easting (hm)	-4.30×10^{-2}	1.50×10^{-2}	−0.264	0.488	2.050

5.0 see Table 2 [27]. In other words, the relationship between the size of a store, as represented by SFA, and the number of people frequenting it, as represented by Volume of Sales, is not linear such that it is not accurate to say that larger stores have larger Volume of Sales. This counter-intuitive finding can be partly explained by the effect of store location. Volume of Sales can be considered to be influenced by the size and demographic characteristics of a store's local customer base which is considered to be dependent on factors such as, amongst others, local population size; ease of access and the extent of competition from other local food retail options.

4.2. Total annual gas demand

Preliminary investigation of total annual gas demand revealed two significant sub-populations of stores without CHP ($N = 89$) and those with a CHP ($N = 34$). This would be expected to be influential as all the CHP systems are gas driven. The sample was divided into those without and with CHP before stepwise multiple linear regression was conducted. It was also found that annual total gas demand was not normally distributed within both sub-populations and that log transformation did not resolve this. Therefore gas demand intensity representing *Gas Consumption*, see Eq. (2) below, was adopted as the dependent variable. The use of gas demand intensity enabled us to determine *Gas Consumption* more efficiently by taking into consideration the store size.

$$\text{Gas Intensity} \left(\frac{\text{kWh}}{\text{m}^2}\right) = \frac{\text{Gas Demand (kWh)}}{\text{SFA } (m^2)} \tag{2}$$

4.2.1. Annual Gas Intensity in stores without a CHP plant

In stores without a CHP, gas is used primarily for warm air heating. Heating demand in these systems is a direct function of the volume of air that is heated and, to a lesser degree because of air recirculation, the outdoor climate conditions.

Through stepwise regression analysis, annual Gas Intensity was found to be significantly influenced by factors reflecting store size, volume and the composition of product lines. From the resultant model, Eq. (3), 29.5% of the variability in *Gas Intensity* is accounted for by the *SFA* of the store and an additional 12.9% is accounted for by the *Ceiling Height* of the store. The addition of the *Number of Trading Floors* of the store increased this by 3.5%, while the addition of the *Food: Non-Food Ratio* of the store increased it by 0.7%.

$$\begin{aligned}\text{Gas Intensity}_{\text{Stores without CHP}} \left(\frac{\text{kWh}}{\text{m}^2}\right) &= 3.8 \times 10^{2} \\ &- 2.0 \times 10^{-2}(\text{SFA } [\text{m}^2]) + 5.8 \times 10^{1}(\text{Food : Non-Food Ratio}) \\ &- 1.7 \times 10^{1}(\text{Ceiling Height [m]}) \\ &- 3.7 \times 10^{1}(\text{No. of Trading Floors})\end{aligned} \tag{3}$$

The model is considered moderate and accounts for 50% (R^2_{adj}) of the variance in *Gas Intensity* ($F(4,84) = 23.65$, $p < 0.001$). *SFA* and *Food: Non-Food Ratio* have the greatest effect on *Gas Intensity*, with standardised β coefficients of −0.373 and 0.325 respectively ($p < 0.001$), while the *Ceiling Height* has a smaller but still significant ($p < 0.01$) effect of −0.283. *No of Trading Floors* has a less significant effect of −0.156 ($p = 0.05$). Whilst all the statistically significant variables have relatively small regression coefficients their B weights indicate relatively strong influence on annual *Gas Intensity*, see Table 4. No collinearity between the independent variables was indicated by the VIF statistics, see Table 4, i.e. VIF for variables are all below 5.0 [27].

It would be expected that *SFA* would not be so influential on gas demand intensity as this already accounts for SFA. However, the above results show that increasing store size results in a small but statistically significant reduction in Gas Intensity, i.e. $-0.02\,\text{kWh/m}^2\,\text{yr}$. This indicates there is a small but significant increase in energy efficiency of larger hypermarkets.

Similar to electricity demand, climatic conditions, in this case represented by *HDD*, were not found to be significant. This is particularly interesting as the predominant use of gas is for warm air heating. It is considered that this indicates that the high proportion of recirculation of air in stores makes good use of internal heat gains and that fabric heat loss is minimal.

Whilst the resultant regression model is only moderate it does show that accounting for the range of product types, i.e. food and non-food, is of a similar order of importance as size and volume when predicting annual gas demand intensity. The results show

Fig. 3. Location of stores with CHP plants.

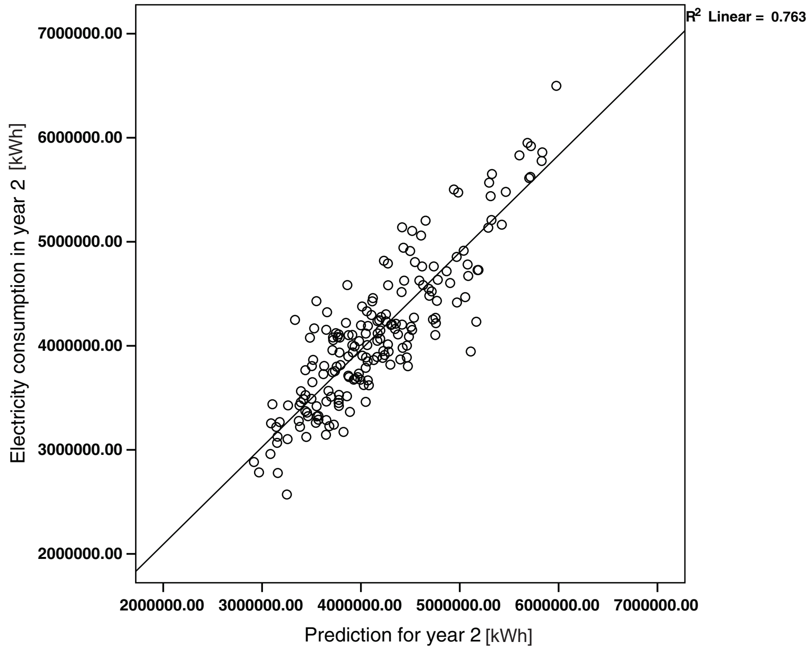

Fig. 4. Validation results for Eq. (1).

that as the amount of sales floor area dedicated to food products, relative to non-food products, increases the gas demand intensity increases. This is considered to partly reflect that some food products are presented in cooled cabinets and that some non-food products can have small heat gains, such as electrical products where TV walls, etc. are in use. Further investigation of the influence of more specific product types, e.g. electrical; clothing; ambient food; etc., could result in better prediction of annual Gas Intensity. Although this model can considered to be of little practical use in its current form it indicates that the volume of air to be conditioned, as represented by store volume, and the heat gains of some non-food products, as indicated by *Food: Non-Food Ratio*, are key factors in gas fuelled energy demands.

4.2.2. Annual Gas Intensity in stores with a CHP plant

In stores with a CHP gas is consumed for heating and to generate electricity. In these stores gas demand is therefore not only driven by the heating demand but also by the amount of electricity that is to be generated. Efficient use of CHP dictates that the use of the system needs to be driven by the demand for heat such that electricity generated is effectively a by-product of generating heat to meet in-store demands. In the context of such efficient CHP management gas demand in stores with CHP could be expected to have similar relationships with factors that affect heat demand as in stores without CHP albeit at a different scale due to comparatively lower efficiency in generating heat in CHP compared to high efficiency boilers.

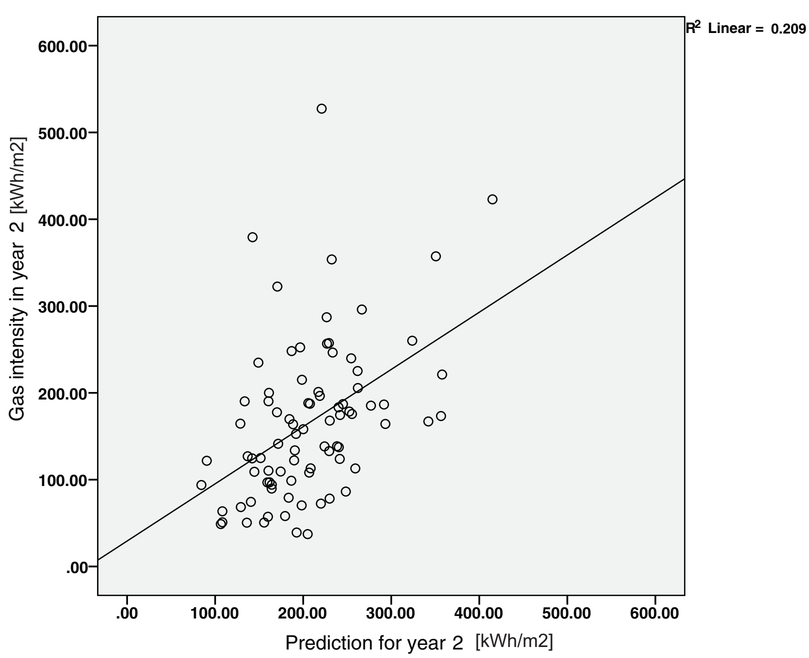

Fig. 5. Validation results for Eq. (3).

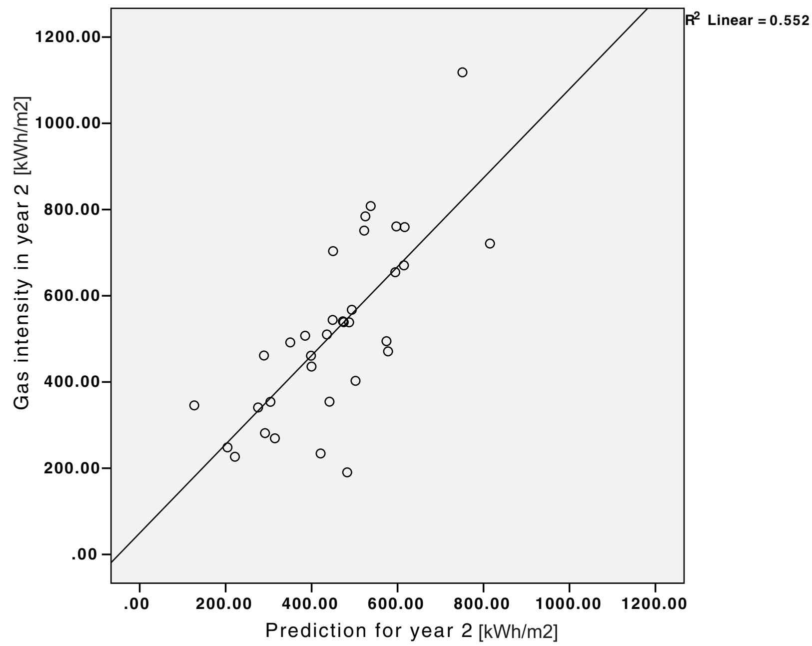

Fig. 6. Validation results for Eq. (4).

Stepwise regression revealed that gas consumption in these stores is a function of size, the electrical capacity or rating of the CHP system, as well as the location of the store and the composition of product lines. From the resultant regression model, Eq. (4) below, 55.3% of the variability in *Gas Intensity* is accounted for by the *SFA* of the building and an additional 16.6% is accounted for by the *Electrical Rating* of the CHP plant. The addition of the *Easting* variable increased this by 4.0%, while the addition of the *Food: Non-Food Ratio* increased it by 3.8%.

$$\text{Gas Intensity}_{\text{Stores with CHP}}\left(\frac{\text{kWh}}{\text{m}^2}\right) = 7.8\times10^2 - 4.9\times10^{-2}(\text{SFA}\ [\text{m}^2]) + 1.2\times10^0(\text{Electrical Rating}\ [\text{kWe}]) - 4.3\times10^{-2}(\text{Easting}\ [\text{hm}]) + 9.0\times10^1(\text{Food : Non-Food Ratio}) \tag{4}$$

This model is considered good and accounts for 77% (R^2_{adj}) of the variance in *Gas Intensity* and is statistically significant (F (4,29) = 25.32, $p < 0.001$). *SFA* has the greatest effect on *Gas Intensity*, with standardised β coefficient of −0.498 while the *Electrical Rating* of the CHP plant has a smaller but still significant effect of 0.344 ($p < 0.001$). The location of the store (*Easting*) has a smaller effect of −0.264 ($p < 0.01$). *Food: Non-Food Ratio* has a less significant effect of 0.298 ($p < 0.05$), see Table 5. No collinearity between the independent variables was indicated by the VIF statistics, see Table 4, i.e. VIF for variables are all below 5.0 [27].

An interesting result is that the Electrical Rating of CHP systems has a significant influence on Gas Intensity. In these stores increasing size of CHP systems result in small, i.e. $R^2_{adj} = 1.2\text{kWh/m}^2\text{yr}$, but statistically important, i.e. beta weight = 0.344, increases in Gas Intensity. Considering that CHP is most efficiently operated as a function of heat demand this finding suggests a degree of inefficiency in the use of these systems during the measured period. This illustrates that the regression method could be useful in identifying inefficient use or system faults.

The finding that location, as represented by Easting, is statistically significant is considered to be a reflection of the sample being small, $N = 34$, and having large number of those stores in the southern part of the UK, see Fig. 3.

4.3. Validation

In order to validate these results, measured energy consumption of the following year was compared to that predicted by the models. These results are presented in Figs. 4–6. The validation of the electricity model shows an R^2 value of 0.76 that agrees with the original 0.75 value. This shows that the electricity consumption of hypermarkets is generally well understood and managed.

The validation of the gas models shows lower R^2 values compared with the original models with values of 0.50 for Gas Intensity in stores without CHP and 0.77 for Gas Intensity in stores without CHP. Some of the outlier stores were investigated further in order to explain this result. The value for the model of Gas Intensity in stores without CHP plants can be partially explained by the subsequent installation of a CHP plant in one of the stores, and the re-calibration of temperature sensors in a further two stores. The value for the model of Gas Intensity in stores with CHP plants can be partially attributed to a faulty CHP plant in one of the stores. The removal of the store from the calculation increases the R^2 value from 0.55 to 0.62. This is exactly how these models can be useful to the organisation; they can identify stores that are consuming higher/lower than the average for further investigation.

4.4. Application of models

The models described in Sections 4.1 and 4.2 enable quick identification of stores that have had significant changes in consumption that warrant further investigation, even though they cannot tell what actions are needed to achieve better performance. They can also be used to identify the impact of efficiency measures. The electrical model accounts for aggregated operational factors explicitly, i.e. Volume of Sales representing the number of customers using a store, while the gas models account for operational factors implicitly. From an organisation's management point of view the starting point in ensuring efficient performance of their building stock is identifying how many and which stores have had significant changes in performance for no apparent reason, and then investigating these on a case-by-case basis. The models reported are considered to provide a reliable first order evaluation of the efficient operation of any hypermarket store within the organisation's stock.

5. Conclusions

Key drivers for energy demand in food retail stores have been identified through literature and examination of a sample of buildings. Following a statistical analysis, significant factors were determined and used to create multiple linear regression models for electricity and gas demands. Significant factors included the sales floor area of the store, the stock composition, and a factor representing the thermo-physical characteristics of the envelope. Two of the key findings are the statistical significance of operational usage factors, represented by Volume of Sales, on annual electricity demand and the absence of any statistically significant operational or weather related factors on annual gas demand.

The results suggest that by knowing as little as four characteristics of a food retail store one can confidently calculate its annual energy demands. Using the models presented in this study, along with the actual consumption of stores, one can isolate stores that are not as efficient as expected and investigate them further to understand the reason for poor performance. At any year-end, stores with measured consumption significantly greater than that predicted by the models can be deemed to have scope for reduction in energy consumption. Even though the models cannot tell what actions are needed to achieve better performance they do enable quick identification of inefficient stores within the stock of hypermarkets. Whilst all the models are based on operational energy consumption, the electrical model accounts for aggregated operational factors explicitly, i.e. Volume of Sales representing the number of customers using a store, while gas models account for operational factors implicitly. From an organisation's management point of view the starting point in ensuring efficient performance of their building stock is identifying how many and which stores are performing inefficiently and then investigating these on a case-by-case basis. The relevance and value of this high level view is supported by the finding that many technical characteristics that would be expected to be influential, such as system performance; weather conditions and building fabric, are not as influential as usage and the primary physical characteristics of size and volume. The models reported are considered to provide a reliable first order evaluation of the efficient operation of any hypermarket store within the organisations stock.

Limitations of this study are that the developed models cannot directly identify particular technical or operational factors that are causing inefficiency. However, whilst being based on data that varies in specificity of some causal factors it does provide empirical and explanatory approaches to assess not only the significance of inefficiencies but also what information and data is important in isolating these. These models can be improved by including more store types in the calculations, collecting energy data values for more than one year, and using more frequent data, such as monthly, weekly or half-hourly. In the future, these models can be developed further and used alongside TM46 [28], as a benchmarking methodology for food retail buildings.

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